An Investigation of Task/Technology Fit and Information Technology Choices in Knowledge Work

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ABSTRACT

This research evaluates the effect of task/technology fit as an antecedent to individuals' IT usage choices. The research is derived broadly from the Technology Acceptance Model (TAM), but differs from previous work on several key conceptual dimensions. Specifically, it focuses on discretionary IT choices that are especially relevant in knowledge work contexts; it assesses task/technology fit from a nonperceptual, task-based perspective; and it focuses on the learning effort required to use IT rather than on a system's ease of use.

A field study was conducted in the public auditing industry to investigate these issues. Fifty-three respondents reported on 93 audits where they chose either a manual or an IT-supported approach to perform the same common, clearly-defined, and well-bounded audit task. The results show that task/technology fit strongly influenced audit supervisors' IT choices. In several audits, however, respondents made IT choices that did not reflect the "best fitting" approach for the particular situation. When individuals avoided using IT even though it had good fit for the task situation, the choice was often due to insufficient IT knowledge and training on the part of either the audit staff or the audit supervisor.

The research contributes to the academic literature on task/technology fit and also leads to several practical implications for managers. For users, time spent learning IT needs to be considered an "investment" rather than a "cost." Moreover, workers not only need to understand how to use IT, but also when (and when not) to use it. Finally, in the systems development area, IS developers need to understand the core information processing requirements of the tasks for which they are building systems in order to implement the appropriate IT functionalities to support those tasks.

INTRODUCTION

Information technology (IT) usage is a core variable in information systems research, since it is necessary (although insufficient) for deriving performance benefits from investments in information technology [24,49]. IT usage research is especially relevant in knowledge work contexts because of the potential productivity gains available through the fit between knowledge work task requirements and IT functionality [17].

One of the most significant recent advances in IT usage research may be Davis's Technology Acceptance Model (TAM), which depicts the importance of potential IT users' perceptions of a system's usefulness and ease of use on their likelihood to use it. The value of TAM as a model for predicting IT usage is demonstrated by the frequency and consistency with which it has been supported empirically, both by Davis and colleagues [11,12,13] and by others [4,35,37].

Although strong relationships between user perceptions and IT usage are widely recognized, TAM's limitations are also becoming apparent. For example, while it is useful for predicting system usage, TAM is less useful for explaining relationships between system usage and task performance. As several researchers have noted, increased usage does not necessarily lead to better performance:

- Increased utilization could be correlated conceptually with either improvement or degradation in performance [33].
- [Usage] is actually undesirable in cases where systems

fail to provide true performance gains [12].

- For a system to have a positive impact [on performance], it must be a satisfactory tool for the critical tasks at hand [25].

Without a clear understanding of whether or not the system provides the capabilities needed for the task, anticipating performance improvements from system usage may not be justified. For example, the apparent lack of productivity improvement in some instances following the adoption of information technology [20,7] may be partially due to use of information technology that does not adequately support the true job needs of the users [42].

A second limitation of TAM is its reliance on perceptual constructs. Individuals may often "misperceive" certain aspects of IT and IT usage. In evaluating IT usefulness, for example, Davis found that individuals significantly misperceived the effectiveness of "what-if" analyses in using a DSS [14] and had difficulty assessing the usefulness of information in decision-making [15]. In evaluating IT usage, Straub, Limayem and Karahanna-Evaristo [47] found that self-reported perceptual measures of system usage had low correlations with computer-recorded measures, which led them to conclude that user perceptions may not match objective assessments.

These two limitations of TAM may stem from the lack of understanding (or evaluation) of whether or not IT is "truly useful" for tasks investigated in IT usage research. Thus, despite the methodological difficulties involved [25], it is apparent that research is needed that evaluates the usefulness and usage of information systems through non-perceptual, "engineering fit" perspectives. That is, it is appropriate to look beyond predictions of an individual's use or non-use of a given information system to also evaluate whether or not individuals choose IT alternatives that are *proper* for, or "fit," the task at hand.

Finally, a third limitation of TAM is that it may not be particularly useful as a general model for improving system acceptance in practice. TAM was developed to predict usage of a given system, not to show how to improve a system's design or to stimulate its use. Furthermore, notions and models of fit, by their very nature, are based to some degree on specific tasks and systems rather than on general principles of computing and information systems. This specificity, in turn, limits the broad usefulness of TAM and task/technology fit in guiding practice.

Given results from research conducted in a particular task and system environment, however, research on fit can lead to concrete and practical recommendations. General implications from this study, for example, suggest that users need to consider time spent learning IT as an "investment" rather than a "cost" and that they also need to understand not only how to use IT, but also when to use it (and when not to). In addition, information systems developers need to understand the core information processing requirements of the tasks for which they are building systems in order to implement the appropriate IT functionalities to support those tasks. These implications are discussed more fully in the "Implications for Practice" section later in the paper.

CONCEPTUAL OVERVIEW

This research evaluates the effect of *task/technology fit* as an antecedent to individuals' *IT usage choices*. It has two primary goals: (1) to demonstrate the feasibility of evaluating task/technology fit from an objective, nonperceptual perspective in a practical, real-world task, and (2) to evaluate the degree to which task/technology fit influences knowledge workers' IT choices. A third, but less direct goal is to evaluate other key factors affecting IT choices in task instances where task/technology appears to be less influential (if they exist).

Although this research is adapted broadly from previous research on TAM, it contains several notable conceptual differences. First, rather than assessing IT usage through traditional measures of system use, it views usage as a discretionary behavioral construct called "IT choices" that is especially relevant in knowledge work contexts. Second, rather than evaluating perceived usefulness, the study evaluates the related concept of task/technology fit, which focuses on non-perceptual dimensions of the available information technology and the task to be performed. Finally, rather than evaluating ease of use, the study focuses on its opposite, which Davis [11] calls "effort to use," by assessing the immediate learning effort required to utilize IT in a particular task instance.

IT Usage versus IT Choices

There are crucial differences in the way the system usage construct has been conceptualized and operationalized in research over the years [24]. Trice and Treacy [49], for example, suggested that system usage studies have typically utilized one of two forms of quantitative measures: "the amount of *effort* expended interacting with an information system or, less frequently ... *information products* generated by the information system per unit of time" (p. 33, emphasis in original). Similarly, Straub, Limayem, and Karahanna-Evaristo [47] also identified two common forms of usage measures, subjective, self-reported measures and objective, computer-recorded measures, which had surprisingly *low* correlations.

As Straub, Limayem, and Karahanna-Evaristo [47] note, this wide diversity of system usage measures causes at least two research problems. First, it is difficult to compare results across studies since there is little consistency regarding either the specific measures used or the underlying constructs they purport to measure. Second, it is difficult to determine which measurement approach is most appropriate for certain circumstances, and the literature does not provide sufficient help in assessing the appropriateness of various measures [24].

Due in part to these concerns over traditional system usage measures, system usage is conceptualized in this study as a construct called "IT choices," which evaluates the *behavioral choices individuals make* regarding IT utilization [27]. Rather than evaluating the extent to which someone uses a system, IT choices evaluate usage as a categorical choice (e.g., use/nonuse of one IT alternative versus another), where every task instance in which a particular system is chosen is considered one equivalent choice, regardless of how intensively the IT is used during that task instance.

IT choices are particularly appropriate for assessing system usage in knowledge work environments because they reflect the important distinction between discretionary and nondiscretionary work components [17]. A notable characteristic of knowledge work is the significant autonomy and flexibility an individual has to choose their task mix, to structure and organize their task processes, and to use or not use certain resources in those tasks [17,20]. One choice knowledge workers often make is whether or not to use information technology in their tasks and, when there are feasible alternative ITs available, which specific one to use [17,27].

Three aspects of the IT choice construct highlight its relevance for research in knowledge work. First, it focuses on users' selections of which (if any) IT to use, clearly a discretionary behavior. Traditional measures, which focus on the extent of hands-on use following an IT choice, may not reflect user discretion since the amount of usage needed to complete the task may be dictated by the alternative chosen. Second, IT choices also reflect worker discretion in task contexts where IT choices and IT usage may be performed by different individuals, that is, where *the IT chooser is not necessarily the IT user*. In these situations, once the chooser chooses, the user again may have little discretion in the amount of subsequent usage that is needed to complete the task. Finally, the IT choice view of system usage recognizes that the choice of a manual process is one type of IT choice, and in some cases, may be the most appropriate task approach [31]. Choosing a manual approach when IT is not useful can lead to improved performance [38,46], while using technology that is not useful for the task may have minimal or even dysfunctional performance effects [12,14,15].

Task/Technology Fit as an Antecedent to IT Choices

The concept of "fit" was developed and used by organizational contingency theorists to explain organizational effectiveness as a function of the extent to which organizational variables fit the context in which the organization operates [50, see 22,51 for reviews). IS researchers, in turn, have investigated the interaction of task and system characteristics and their effects on information system usage and task performance. As Sambamurthy [44] suggests, there is a fundamental conceptual linkage between task/technology fit and performance:

> The conceptual underpinning of [task/technology] models is that effective task performance imposes a set of task requirements; an intervention technology that provides capabilities to match these task requirements would enhance task performance. Further, technologies that do not fully match the task requirements would be ineffective in enhancing performance (pp. 1-2).

This linkage between fit and performance is consistently reflected in IS research at various levels of analysis. At the *work group level*, for example, Davis, Pearce and Randolf [16] and Sambamurthy [44] found significant relationships between variant forms of fit and group performance. At the *job level*, Goodhue [25] evaluated a fit construct called "IS satisfactoriness" ("the correspondence between job requirements and IS functionality, mediated by individual abilities" (p. 13)), and found that satisfactoriness was a surrogate for system performance.

At an *individual level*, Srinivasan [46] used a behavioral approach that evaluated (1) the fit between the technical sophistication of a model-based corporate planning information system and user needs and (2) the impact of fit on system effectiveness. Notably, he found that system use and system effectiveness may, in fact, be "two entirely different phenomena" (p. 252), contrary to IS research that often considers system use to be a surrogate for system success [25]. Finally, Vessey and Galletta [52] used a cognitive approach at the individual level (called "cognitive fit") to evaluate the fit between the information processing requirements of a task, the capabilities of IT available for the task, and a user's mental representation of the task and technology. Suggesting that performance is best when dimensions of the task, technology, and individual are all aligned, they found that users whose mental representations of the problem "matched" the problem representation tended to use the available technology more effectively, resulting in faster and more accurate decisions.

While these and other studies suggest a relationship between fit and performance, they often suggest a direct causal link: better fit leads to better performance [25,27, 44,52]. The premise seems to be that if there is fit between task and technology, performance will increase due to use of the "fitting" technology. The inherent weakness in this premise, however, is that it does not acknowledge individuals in discretionary usage environments who make explicit choices of whether or not to use the technology. Simply having a "good fit" technology available may not lead to improved performance, since the individual may choose not to use it [25,46]. As a result, the *potential* benefit of more useful technological capabilities or features may not be transformed into actual performance gains by users. As Srinivasan [46] recognizes:

> The mere presence of a particular technical feature is a poor indication of [system effectiveness] ... If a feature is incorporated into a particular system and is not used, the assumption can be made that such a system is equally sophisticated as one that does not incorporate that feature. (p. 249).

In sum, a contingency theory suggesting that task/technology fit leads to improved performance may not hold in task contexts where users have discretion over the use or nonuse of IT. Rather than expecting improved performance due to "good-fitting" IT, it may be appropriate to step back and evaluate whether individuals even tend to choose "useful" IT alternatives.

Proposition #1: Task/technology fit influences individuals' choices of whether or not to use information technology in their tasks.

P1 is the corollary to the relationship described in TAM between perceived usefulness (PU) and system usage, where an individual's perception of task/technology fit is a direct antecedent to their attitude towards using the IT and, in turn, to their system usage. The key difference is that the current research evaluates task/technology fit from an "engineering" [25] or "objective" [13] perspective rather than using individuals' perceptions of IT usefulness as a surrogate for fit [25].

To evaluate task/technology fit in an objective or engineering sense, this research uses a perspective of fit that Venkatraman [51] calls "fit as matching," which suggests that one can evaluate the extent to which a technology matches, or fits, the needs of the task based on the important characteristics of a task to be performed and the capabilities of technologies available for the task [also 44]. One critical dimension of this perspective is that characteristics of the individual are removed entirely from the consideration of "good" or "bad" fit. In other words, the fit of a given IT in a given task is unrelated to any particular IT user in that task instance and is simply a function of whether or not the characteristics of a given task would be supported effectively through use of information technology.

Perhaps the most difficult aspect of evaluating an engineering fit is determining how "useful" a given technology is for a specific task. In a lengthy theoretical discussion of certain benefits and costs of IT usage, Nance [38] demonstrated how the *volume of data to be processed* is one key task characteristic that influences the fit of information technology in certain types of data processing tasks. One of the well-known benefits of information technology is the ability to store, process, and retrieve large amounts of information more quickly and inexpensively than is possible without such systems [19,27,45]. However, IT use also requires time-consuming activities such as installing and/or booting software, accessing data files, and planning the use of IT. These types of activities represent fixed "overhead" costs that are required simply to use IT and may have little or nothing to do with performing direct task activities [17].

Due to these cost/benefit tradeoffs, when the volume of data to be processed is high, the processing speed of IT more than offsets the IT overhead costs, so the IT alternative has better task/technology fit than a manual alternative. But when the data volume is small, IT's processing speed may not compensate for the IT overhead and a manual approach would have better fit because it avoids the IT costs. In short, this analysis suggests that the usefulness (or fit) of IT, compared to manual approaches, increases as the amount of data to be processed increases.

If individuals choose to use or not use information technology based on the "true" usefulness of the technology for the task, then their IT choices in some types of data processing tasks should be influenced by the volume of data to be processed. This leads to the first hypothesis:

H1 For data processing-intensive tasks, the volume of data to be processed affects the choice of manual versus IT-supported task approaches.

H1a. Manual alternatives are used when the volume of data to be processed is low.

H1b. IT-supported alternatives are used when the volume of data to be processed is high.

Research on TAM and other behavioral models of antecedents to system usage suggests that individuals tend to make IT usage choices based on their perceptions of system usefulness. In fact, perceived usefulness may be the primary factor affecting usage [11,12,35]. As long as perceptions of usefulness match objective assessments of task/technology fit (which may not always be the case [14,15,47]), task/technology fit may directly influence individuals' choices of whether or not to use IT.

Learning Effort as an Antecedent to IT Choices

However, in addition to task/technology fit, other factors may also be influential. In particular, the user's familiarity or comfort with the available IT may be important. Although Davis [11] suggests that users may be willing to tolerate (or learn to use) a difficult interface on occasion in order to access needed functionality, learning issues are widely believed to affect IT usage [9,39,40,54].

As part of the learning process, knowledge workers often explore IT capabilities to learn about ways IT can be used, the relative usefulness of alternative ITs for specific tasks, and the benefits that can be obtained [9]. Learning is "a relatively permanent change in behavior occurring as a result of experience" [39 p. 505], and users who explore a wider range of capabilities are likely to adapt their use of IT over time in order to utilize the most useful capabilities [9,27,43]. However, in the short-term, someone facing an immediate task may also consider the effort required to use the IT, perhaps with little regard to functionality [41], and they may choose an easier but less useful alternative for short-term expediency [38].

Although a wide variety of research on user learning, education, and training has been conducted (see [39] for a review), the effect of immediate learning effort on task-level IT usage choices has not been investigated directly. Illustrative of prior research is Nelson and Cheney's [40] major study that found a direct relationship between computer-related training and likelihood of IT adoption and use. Not atypically, they evaluated user abilities in terms of a user's *existing skill set* at the time of the system usage, an approach that assesses, in effect, the sunk costs of training ("have you taken the time to learn?"). The current research takes a unique approach to assessing learning effects by evaluating the *immediate learning effort* required by someone facing a specific task, an approach that emphasizes the marginal training costs ("are you willing to take the time to learn now?") for an individual considering whether or not to use IT in the upcoming task instance.

Proposition #2: The immediate learning effort required to use information technology may, in some instances, influence individuals' choices of whether or not to use the IT in their immediate tasks.

P2 is the corollary to the relationships described in TAM between perceived ease of use (PEU), perceived usefulness and system usage. TAM suggests that PEU does not influence system usage as strongly as PU and that users may be willing to tolerate difficult system interfaces in order to obtain functionality needed for their tasks [11]. Nevertheless, users do evaluate how easy or difficult it would be to use a given IT alternative in their tasks and they may choose not to use information technology even though it has useful functionality for the task [8,41].

Thus, there may be instances when an individual does not choose the IT alternative that is the most useful, or has the best fit, for the particular task circumstances. Drawing again from TAM, the key secondary factor influencing IT choices in these instances may be the immediate learning required to use IT. This leads to the second study hypothesis:

H2 In instances where task/technology fit does not predict an individual's IT choice, the IT learning costs are a relevant factor in the choice.

H2a. In instances where manual alternatives are chosen even though IT has good task/technology fit, there is high learning effort required to use the IT.

H2b. In task instances where information technology alternatives are chosen even though IT does not have good task/technology fit, there is low learning effort required to use the IT.

This hypothesis is highly exploratory. The extent to which individuals choose alternatives other than the best fitting approach has not been investigated to date, so there is no *a priori* evidence of the frequency of these types of IT choices. It is possible that no instances of "poor fitting" choices may be observed, since task/technology fit may be found to drive IT choices entirely. The likelihood of such a result may be small, though, based on evidence from previous research on TAM and other studies depicting the effects of learning and training on IT usage.

RESEARCH CONTEXT

This research is conducted in the knowledge work domain of public auditing, which contains two key contextual dimensions that make it particularly relevant for the issues investigated. First, even though auditors are constrained both by external requirements [e.g., 1,2,3] and internal policies [10,30], many auditing tasks rely on a *high degree of individual discretion* over choices of the process and tools to be used [5,28,29]. Two critical choices individual auditors make in any audit are which audit procedures to perform to accomplish specific objectives [1,2,36,53] and which specific audit tools to use in performing those procedures [5,34].

The second relevant aspect of the auditing environment is the *clarity and observability of the IT choices* that are made in audits. The audit supervisor, who is an active member of the audit team, chooses both the specific tasks to be performed and the tools to be used. The supervisor formally documents the choices made and assigns the tasks and techniques to staff auditors who execute them as prescribed. Thus, the task and tool choices are (1) clearly identifiable and verifiable, (2) distinct from the tool usage and task execution, and (3) made by an individual who may not necessarily be the actual user of the information technology.

Although research has not directly addressed the fundamental issue of the costs and benefits of alternative decision aids used in audits [6], at least two studies have evaluated the general usage of IT in the public auditing industry. Gogan [23] assessed the relationship between access to IT and individuals' IT usage in Big 8 auditing firms and found that auditors in organizations with greater access to personal computers spent more time and used them for a wider range of audit procedures than individuals in organizations with lower access. Lovata [34] investigated the use of various computer-assisted audit techniques (CAATs) and the accounting areas (e.g., payroll, receivables) in which they were used. Among Big 8 firms, she found that (1) some firms used CAATs more frequently than others, (2) Generalized Audit Software (GAS) was the most common CAAT used overall, and (3) Accounts Receivable was the most common accounting area of CAAT usage. All of these findings provide useful insights for the current study, but her caveats regarding the study's limitations may be even more significant, as they note that the study did not "attempt to evaluate the appropriateness of when firms apply each technique" and that the results did not "reflect differences in effectiveness or efficiency" (p. 67) across organizations. These observations relate directly to the current research because they reflect the basic principles of task/technology fit.

METHODOLOGY

The study is a field study using audit supervisors from local offices of the six largest public auditing firms, known as the "Big 6," located in a large midwestern city. Mailed questionnaires and follow-up telephone interviews were used to evaluate audit supervisors' IT choices in recent audits. Using an audit level of analysis, the questionnaire asked respondents to describe up to three recent audits in which they were involved in supervisory activities and in which they used a different technology alternative, one manual and two IT-supported techniques, to complete a single, specific audit task.

Based on the results of preliminary field work, an *accounts receivable (A/R) high-dollar account selection* task was chosen as the primary audit procedure to be investigated. This is a simple information retrieval activity where the auditor extracts from the client database a set of records that comprises a substantial portion of the total A/R account balance in order to perform subsequent tests to confirm the accuracy and collectibility of those balances. The study only used the initial selection portion of the account analysis procedure; subsequent testing activities were excluded.

In a manual approach to the audit task, the auditor scans a hard copy list (sorted alphabetically, by invoice number, etc.) and notes the desired accounts. In an IT-supported approach, the auditor uses software functionality either to sort a file on a specified field or to extract records using database querying capabilities [18]. Since the audit team can obtain this software functionality through either audit firm software or client software, the research sought to determine if any notable differences existed between these two IT-supported alternatives. Therefore, respondents were asked to report on three different audits, one where the task was completed manually, and two others, if possible, where they had used audit software and client software respectively. Subsequent analysis of the two IT-supported alternatives revealed essentially no differences in any variables, so they were ultimately combined, resulting in the study comparing manual approaches to IT-supported approaches to the audit task.

The clarity and simplicity of a high-dollar account identification task makes it especially useful for the purposes of this research. It is a common data processing task in the industry, so study participants across organizations have a common understanding of the specific research task, despite firm-level differences in terminology. It also has well-defined boundaries and clear output requirements (the auditor must generate the desired — correct — list of accounts), which is desireable for research but uncommon in many knowledge work tasks [17]. Finally, the audit team has significant discretion in the choice of which particular tools and techniques they use to generate the outputs.

Instrument Development and Pretesting

Two phases of instrument development and pretesting preceded the full data collection. In the first phase, audit supervisors from local offices of local, regional, and national organizations were interviewed and/or completed a questionnaire discussing the appropriateness of various audit tasks for the research. Intended to identify a common audit task where manual or IT approaches can be used, this first phase of pretesting resulted in the selection of the high-dollar A/R selection test described previously. The second phase of the preliminary field work then involved revising and pretesting the questionnaire instrument in order to establish the validity of the study instrument and measures. Respondents drawn from the same population as the sample used in the full study completed the questionnaire in the presence of the researcher. Six audit managers, two from each of three Big 6 firms, provided usable data on 12 different audits in which they recently completed an A/R high-dollar account analysis.

Instrument and measurement validity were evaluated qualitatively using direct observation of respondents completing the questionnaire, plus in-depth semi-structured interviews after they finished. Respondents consistently agreed that the questionnaire terminology was precise enough to convey the intended meaning, yet generic enough not to be organization-specific. Respondents also confirmed that factors relevant to their decision to use or not use information technology in their audits were fully covered in the instrument and that the measurement scales used were reasonable not only for the reported audit, but also for their overall audit portfolio.

Full Data Collection

Finally, the primary phase of the research involved administration of the questionnaire instrument and follow-up telephone interviews. Audit partners from each firm authorized to commit the personnel resources needed for the study provided organizational participation commitments. An authorized contact at each firm developed a list of audit supervisors in their firm who were best qualified to complete the questionnaire and informed them that they had been named to complete and return the questionnaire as part of their firm's participation in the study.

Individualized cover letters and questionnaires coded to match the names on the participant lists were then mailed to each person. After the data from a returned questionnaire was recorded, the respondent was interviewed in a follow-up telephone call lasting up to 30 minutes. Follow-up comments were recorded on the questionnaire, the respondent was asked to confirm the accuracy of all comments or clarifications, and the database entry was updated as needed.

Variables

As discussed in the task/technology fit conceptualization, the choice of whether to use a manual or an IT-supported alternative for certain types of data processing tasks was hypothesized in H1 to be dependent upon the volume of data to be processed. **Volume of data** was operationalized in the study as the size of the client's A/R file and was measured by the number of records in the file (rounded to the nearest 100, 1000 or 10,000).

H2 hypothesized that in instances where volume of data did not predict the IT choice, if there were any, the **IT learning costs** would be a relevant factor in the choice. Under the assumption that sample sizes for H2 would be large enough for statistical analyses, this construct was operationalized as the amount of learning time that was required before the assigned auditor(s) could begin the actual process of identifying high-dollar accounts in a particular audit. Drawing on distinctions Nelson [39] makes between education and training, two types of learning were combined to measure total immediate learning effort. *General literacy education* evaluated time required to obtain an understanding of broad technological principles that might apply to a range of tasks. *Task-specific training* evaluated time required to learn how to tailor, or implement, auditor(s)' general IT knowledge within a particular audit. In order to compare learning time requirements between manual and IT alternatives within a particular audit, it was necessary to evaluate not only the learning times for the IT choice that was made, but also the learning time *that would have been required for the nonchosen alternative.*

Auditors, as human beings, are subject to the same biases and errors in judgment as anybody else, and asking them to estimate time requirements for behaviors they chose not to do obviously raises concern over data reliability. However, audit supervisors were chosen as study subjects precisely because of their skill and expertise in this area. One primary job responsibility of an audit supervisor is to formally estimate, track, and document, on a regular basis, planned and actual time and costs for a variety of task activities. Since this is a very different work requirement compared to most industries, the audit supervisor respondents participating in this study are probably more uniquely qualified to provide such difficult estimates than any other potential subject pool.

Finally, given the exploratory nature of H2, the questionnaire included a free-form item asking respondents to describe the **one or two factors that were most influential** in their IT choice; the follow-up phone interview then probed for elaboration.

RESULTS

Table 1 provides a summary of the response distribution by organization. Of the 73 individuals in the mailed sample, 55 completed and returned the questionnaire, an overall response rate of 75.3%. Based on comments written on the questionnaire and/or raised in the telephone interviews, two questionnaires from Firm 4 were judged to be unusable since the respondents indicated that they had no familiarity with the specified audit task. After removing these two responses, the final sample contained responses from 53 individuals, representing a 72.6% usable response rate.

Nonrespondent Analysis

During the data collection period, follow-up calls were made twice to most nonrespondents to encourage their participation. Intended to encourage individuals to return the questionnaire, the discussions were also useful for assessing nonresponse bias. Fifteen of the 18 nonresponses were accounted for through specific explanations, leaving only three of the 73 mailed questionnaires (4.1%) neither returned

TABLE 1

Profile of Organizational Responses

Firm Number*	Qstnrs. Sent	Qstnrs. Received	Response Rate
1	10	7	70.0%
2	12	10	83.3%
3	10	10	100.0%
4	14	9	64.3$
5	15	11	73.3%
6	12	8	66.7%
Total	73	55	75.3%
Mean	12.2	9.2	

* Randomly numbered for confidentiality.

TABLE 2

Profile of Respondent and Audit Samples

	RESPONDENT JOB TITLES				AUDIT APPROACHES		
Firm Number	Senior Managers	Audit Managers	Audit Seniors	Total Respondents	Manual	Software	Total Audits
1	2	5	0	7	6	6	12
2	3	7	0	10	7	11	18
3	1	6	3	10	10	5	15
4	1	5	1	7	7	7	14
5	2	7	2	11	10	10	20
6	7	1	0	8	6	8	14
Total	16	31	6	53	46	47	93
Mean	2.7	5.2	1.0	8.9	7.7	7.8	15.5
% of Total	30.2%	58.5%	11.3%	100.0%	49.5%	50.5%	100.0%

nor explained. Combined with the explained nonresponses, this small percentage of unaccounted-for questionnaires suggests that there was no systematic bias between respondents and non-respondents.

Final Sample Profile

Table 2 provides a profile of respondents' job titles by organization and the distribution of manual and IT-supported audits they reported. A manual (paper list) approach was used to identify high-dollar accounts in 46 audits (49.5%), while software was used in the other 47. Respondents were primarily senior managers (30.2%) and audit managers (58.5%) who had been employed in their firms for an average of 7.3 years and in the public auditing field for 7.5 years. Forty-nine of the 53 respondents (93%) had worked in the industry for five years or more, with 13 subjects (25%) having 10 or more years of industry experience. This profile suggests that the sample appears to have been drawn from the target population of auditors who have specific supervisory responsibilities. Audit partners, who tend to be more involved with general planning and review activities than with client-specific audit procedures and techniques, served as primary site contacts but did not participate as subjects. Staff auditors, who typically carry out assigned tasks but are not involved in supervisory and planning activities, also were not represented in the sample.

Hypothesis Tests

The data were analyzed both quantitatively and qualitatively. Formal statistical analyses were used to evaluate the first study hypothesis. Additional qualitative analyses were used to gain deeper insight into H2 in instances when individuals occasionally chose not to use the approach that had the best task/technology fit for the task.

Discriminant analyses, crosstabulations, and chi-square tests were used to evaluate the relationships described in H1 between file size and IT choices. The file size data in the reported audits was highly skewed to the right, as suggested by the descriptive statistics shown in Table 3. Since the file size data violated a distribution normality assumption required in discriminant analysis, which is not uncommon among naturally occurring groups [48], a series of discriminant analyses were performed. The file size data were transformed into dichotomous categories representing "small" and "large" files, based on a given "threshold" value for the number of records (e.g., fewer than 1000 versus 1000 or more), a discriminant analysis with cross-validation [26, 32] was run using these discrete values as the predictor variable,[1] and a chi-square crosstabulation was used to determine the statistical significance of the relationship between file size and IT choices. The file sizes were then reclassified as small or large using a slightly different threshold and another set of discriminant and chi-square analyses were run. This process was repeated for all likely file size thresholds represented in the data sample.

The highest proportion classified correctly was 83.9% (78 of 93 correct), which occurred when files containing fewer than 800 records were categorized as small and files containing 800 or more records were considered large. The proportion correctly classified steadily decreased as the test

[1] Although discrete predictor variables may not be as robust as normally distributed quantitative variables in some circumstances, they can be used in discriminant analysis [21]. Moreover, analytical flexibility is generally greater for discrete predictor variables with dichotomous categories, as in this case, than for discrete variables with more than two levels [48].

TABLE 3

Summary Statistics of File Size Data (Number of Records)

	Mean	Median	Std. Dev.	Min.	Max.
All Audits	19,071	1,000	68,503	25	600,000
Manual Audits	824	200	1696	25	10,000
Software Audits	36,930	3,500	93,401	100	600,000

threshold diverged in either direction from this peak. Using this classification as the highest degree of fit between the file size task characteristic and the IT choice, H1 was supported. The chi-square value of 44.253 was significant at $p < .001$. When the volume of data to be processed was low (i.e., the client's A/R file was small), audit supervisors tended to choose a manual alternative; when the volume of data was high, they tended to choose a software alternative.

Although the tendency to make IT choices based on task/technology fit was evident, there were exceptions when individuals chose a manual approach for large files or an IT-supported approach for small files. Even when the highest correct classification rate was used, 15 of the 93 audits did not reflect file size as a predictor of the IT choice. In three instances, audit supervisors chose to use IT on small files, which contained 100, 200, and 400 records respectively (roughly two to eight pages of hard copy lists). In the other twelve audits, the audit supervisors chose a manual approach for large files, ranging from 800 to as many as 10,000 records, which required scanning up to 200 pages by hand.

Given the discovery of these IT choices that do not reflect task/technology fit, H2 suggests that the immediate learning effort may be a major antecedent factor. Because the exploratory nature of H2 resulted in a small sample of audits, the time estimate data comparing one alternative to another was insufficient to warrant formal quantitative analyses. Instead, data from the free-form item asking respondents to describe the factors that most influenced their IT choice was analyzed qualitatively to evaluate the underlying factors that led the audit supervisor to select the chosen approach.

These respondent comments, which are summarized in Table 3, provided notable insight into respondents' choices. In explaining the three software choices for small files, for example, nobody focused on learning or training issues. Instead, respondents discussed three different issues: maintaining a "high-tech" image, a lack of set up effort required, and a need to do a series of tasks only possible through use of IT.

On the other hand, in explaining the 12 manual choices for large files, several "cost" issues did appear to play a significant role. In terms of immediate learning costs, which was the study focus, a number of respondents commented directly on the inadequacy of staff capabilities to use software-supported audit tests. Respondents in audits #6, #11, #13, and #15 all attributed their choices directly to insufficient software training or understanding on the part of the audit staff.

Evaluation of another aspect of the questionnaires, however, revealed a striking related finding: despite the fact that they were familiar with the software approach for identifying high-dollar accounts and occasionally used software for other tasks, respondents (i.e., the IT choosers) in six other audits (#4, 5, 7, 8, 12 and 14) had never personally worked on an A/R audit where audit software (the most common type of software used overall) was used to identify high-dollar accounts. Three (#4, 8 and 14) had never worked on an A/R audit where any type of software had been used in this task. Thus, a second underlying, and less obvious, "learning cost" factor that appears to have contributed to several of these manual choices may be a lack of software training or experience *on the part of the audit supervisor* who made the decision to use the manual approach.

A third "cost" that appears to have had an impact on these manual choices is not necessarily a learning cost, but is more a form of *implementation cost.* In at least six of the audits (#7, 9, 10, 12, 13 and 14), respondents suggested that difficulties associated with setting up or matching the audit firm's technology for the client's technical environment precluded them from using an automated audit approach. While several of these respondents were also discussed above as having had little or no training in these types of audit activities, others were very familiar with automated account identification procedures. The respondent in audit #10, for example, reported having performed at least 40 A/R audits over 13 years where software was used, while the respondent in audit #13 reported having used audit software in at least 180 A/R audits over 12 years. This level of personal experience clearly lends credence to these respondents' technological, as opposed to learning effort, explanations for choosing manual approaches in these audit circumstances.

DISCUSSION

One objective of this study was to demonstrate the feasibility of evaluating task/technology fit from a non-

TABLE 4

Summary of Respondent Qualitative Explanations

Audit	# Records	Respondent Explanation
		Software Choices in Small Files
1	100	The software was developed and we had an established practice of using it. It is not more efficient but looks more technologically advanced to the client.
2	200	Ability of the client to download the file with Excel-compatible data eliminated set-up time on our part.
3	400	We had a need to do a statistical evaluation of errors and efficiency in the task that would not have been possible had we not used software.
		Manual Choices in Large Files
4	800	The search was limited to a few customers generating the most dollar volume.
5	1000	We were able to use the results and resources of the client's internal audit function.
6	1000	We had a lack of experience with audit and/or client software.
7	1000	The client was able to produce a readily accessible paper list of accounts that reduced our recurring start-up time to one hour.
8	1000	There was greater efficiency in obtaining the needed information.
9	1000	This was a very complex system that contained bad data in the full file and it was very difficult to figure out how to do the test.
10	1000	The client's recent change to process A/R in-house would have resulted in our needing to modify our existing software. Given time constraints caused by the conversion, we elected to perform a manual selection and to go back to a software-based selection next year.
11	2000	No staff were assigned with necessary training.
12	2500	It was the only way technologically possible (within a reasonable time frame) based on client system constraints. We had a problem linking multi-site files together to download.
13	4000	Short time frame required to perform the audit procedures, coupled with the complexity of the client's EDP system and the audit team's lack of familiarity with the system, led to great uncertainty about problems with the software approach that may arise.
14	5000	It was easier to just flip through a paper list, rather than set up and convert the data.
15	10,000	People are not computer literate in my office, and the staff training was not sufficient.

perceptual perspective, based on the costs and benefits of information technology relative to the volume of data to be processed, with no consideration of the individual (i.e., perceptions, skills, etc.) embedded in the assessment of fit. The second objective then sought to evaluate the effect of task/technology fit as an antecedent to knowledge workers' IT choices. For the task selected in this study, which is a common, small, clearly bounded audit task, the results indicate that fit did appear to influence respondents' task-level IT choices. Finally, the third exploratory objective sought explanations for situations that indicated respondents' IT choices did not reflect the best fitting alternative. In these instances, many of the explanations focused on insufficient training (and, in turn, unwillingness to learn "on the spot") on the part of either the staff auditors or the audit supervisor making the IT choice. In a few instances, respondents also described technological implementation difficulties that prevented them from choosing an IT-supported alternative.

Implications for Management

As noted earlier in the paper, the concept of task/technology fit and the TAM model of predicting IT usage was not originally designed for practical application. For example, it is not particularly surprising to discover that the volume of data to be processed influences whether or not an individual chooses to use IT, since processing large amounts of data is, after all, a well-known application for information technology. Despite these conceptual limitations, however, several implications for practice can be drawn from this study.

First, it is notable that knowledge workers' (in this case auditors) choices of whether or not to use IT occasionally were based on factors other than the underlying usefulness (i.e., task/technology fit) of the available technology. It suggests that even when faced with a clear and simple task, knowledge workers may not choose the most useful alternative available. In some instances, these choices are made simply because the individual is not willing to learn the more useful approach. This represents a very short-sighted point of view, since time spent learning a more useful (and presumably more efficient) way of doing work represents an "investment" that will provide returns over time; it is not necessarily a "cost" to be incurred in the short-term. This investment rather than cost perspective of software training and learning is a crucial philosophy that managers need to adopt and disseminate in their organizations if they want to encourage and stimulate their workforce to become more IT-literate.

A second practical implication of this research can be drawn from the frequency of the "inappropriate" IT choices that were seen in this study (15 of 93 audits, or 16%). The study task was intentionally chosen because of the relative ease in evaluating task/technology fit: a single task characteristic, file size, and clear IT alternatives, use or nonuse of software. In such a situation where task and technology characteristics are so obvious, practicing individuals in industry should be expected to see the fit and choose IT accordingly (as the majority tended to do in this study). The fact that there are *any* choices of less useful approaches in such an obvious task setting, however, suggests that such choices may be much more frequent in other tasks where fit is less clear-cut and individuals have a more difficult time evaluating fit accurately. Thus, it is apparent that managers must not only be aware of their workforce's knowledge of IT concepts, but must also train their staff on when to apply (and when not to apply) IT in their tasks. This extends far beyond IT-training as it also includes both job training and the ability to discern how and when different IT functionalities support various job activities.

Finally, a third implication of these research findings for practice relates not to IT usage, but to information systems development. The entire notion of task/technology fit rests on an assumption that systems that best fit the needs of a task, if used, will improve the performance of the user in that task. To develop systems that are capable of improving user performance, the systems development team must understand the key information processing needs of the task(s) the users will perform and must design into the new application those key information processing functionalities that support these requirements. By developing an application with high task/system fit, they ensure that the appropriate system capabilities are provided to support the unique needs of a given task, which improves the user's subsequent performance in completing the task. Without appropriate functionalities built into delivered systems, organizations have little or no hope of improving worker performance through information technology.

Implications for Research

This discovery of IT usage choices that do not reflect task/technology fit adds to recent research on individuals' perceptions of IT usefulness [12], cognitive fit [52] and IT usage [47]. It also highlights an important area for future research on information system usage: although perceptions of IT usefulness and ease of use may well affect IT usage, the degree to which those perceptions match objective, engineering-based assessments of IT is not clear. Recent evidence raises some doubt about individuals' perceptual accuracy. Until research demonstrates that individuals do tend to form accurate perceptions across a variety of tasks and task environments, the question of whether or not the full processing benefits of information technology are utilized by individuals and organizations may remain unanswered.

Like most studies, key limitations of the research must be considered. The major limitation of the study involves the generalizability of the results to other tasks and contexts. This study's narrow focus on a single task in the specific knowledge work domain of auditing raises questions as to whether many of the issues addressed here are appropriate for other tasks or industries. But as discussed above, the very simple data extraction task used in the research may make the findings more generalizable than appears at first glance since users in many different task contexts may encounter similar forms of this generic data retrieval task. Extending this research to other task domains is an obvious area for subsequent research.

Finally, and in closing, another limitation is the study's focus on short-term, immediate learning assessments. Prior research has often recognized the long-term, exploratory and experimental nature of many users' learning efforts. Similarly, the innovation diffusion literature highlights the nature of technology adoption *over time*, where users often fall on different segments of the adoption curve. By focusing on the short-term nature of users' learning assessments and IT usage behavior, this research fails to capture dimensions of learning that lead to longer-term changes in user behavior over time. It also fails to capture individuals' training "investment" versus "cost" assessments that were discussed earlier. This limitation highlights a third important area for future research, as it suggests a need for research that evaluates task perspectives extending beyond the single, short-time frame task evaluated in this study.

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